Energy Efficient Resource Allocation for Wireless Power Transfer Enabled Collaborative Mobile Clouds

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***Abstract*—In order to fully enjoy high rate broadband multimedia services, prolonging the battery lifetime of user equipment is critical for mobile users, especially for smartphone users. In this work, the problem of distributing cellular data via a wireless power transfer enabled collaborative mobile cloud (WeCMC) in an energy efficient manner is investigated. WeCMC is formed by a group of users who have both functionalities of information decoding and energy harvesting, and are interested for cooperating in downloading content from the operators. Through Device-to-Device communications, the users inside WeCMC are able to cooperate during the downloading procedure and offload data from the base station to other WeCMC members. When considering MIMO wireless channel and wireless power transfer, an efficient algorithm is presented to optimally schedule the data offloading and radio resources in order to maximize energy efficiency as well as fairness among mobile users. Specifically, the proposed framework takes energy minimization and Quality of Service (QoS) requirement into consideration. Performance evaluations demonstrate that a significant energy saving gain can be achieved by the proposed schemes.**

***Index Terms*—energy efficiency; collaborative mobile clouds; content distribution; wireless power transfer; resources allocation**

I. Introduction

The explosive growth of the smartphone industry, multimedia services and mobile applications heavily relies on high speed data transmission. Although the rapidly-increasing high speed wireless networks are continually affecting our life and even changing our daily behaviors, the demand for high data rate services is straining the current networks as well as draining the batteries of mobile terminals (MTs) much faster than before. Meanwhile, it is widely acknowledged that the current cellular structure has difficulties in dealing with the traffic increase as well as the spectrum crunch. Therefore, tackling the energy and spectrum crisis urgently requires the development of future wireless network architecture.

On the other hand, today's laptops, smartphones and tablets have large storage capacities, which are rapidly growing but typically under-utilized. The highly developed computing units of these devices are also capable of processing much more complicated tasks, which is often reflected in their energy consumption. Consequently, development of MTs in the design of an energy and cost efficient platform for high data rate services is taking place at a fast rate, and is one of the important trends when evaluating the next generation communication systems. Offloading or caching cellular data is one of the potential solutions for providing the efficient data services with limited costs. Due to the proliferation of smartphone technology, offloading cellular network has received increasing attention during recent years. Several efforts have been dedicated to designing novel data offloading frameworks via Femtocells or WiFi networks, e.g [1] and [2].

Offloading cellular data to small cells or WiFi networks is usually restricted by network deployment and it also relies on the availability of Internet access [3]. Benefiting from the delay-tolerant nature of today's non-real time applications, service providers may directly send the content to the users, which reduces cellular data traffic as well as operation costs. Therefore, in addition to infrastructure data downloading, mobile data offloading through ad-hoc networks, such as Device-to-Device (D2D)/ Machine-to-Machine (M2M) systems, is also a very attractive technique in the light of distributing the delay-tolerant or non-real time data to a number of MTs. In [3], the authors utilize the concept of mobile social networks and study the user-set selection problem to minimize mobile data traffic from both content and social domains. In order to reduce energy consumption of the Base Station (BS), the authors of [4] propose a novel mobile traffic offloading scheme, where a new network node dubbed the green content broker is introduced to arrange content delivery between source and destination. In [5], a content distribution framework called the collaborative mobile clouds (CMC) is introduced. A CMC, as presented in Fig. 1, consists of a number of MTs that can download from the BS and share the content in a cooperative

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manner. Applying the mobile clouds framework, the content can be separated into several segments or chunks. The BS offloads different chunks to selected MTs, after which the MTs exchange these chunks via D2D communications [6]. Therefore, instead of transmitting entire data contents to each requested MT, only a few data streams are delivered through the cellular networks. The CMC is seen to reduce energy consumption of the MTs during the downloading process [5] [7]. In addition, such a cooperative architecture is also applicable to smart grid [8] and the vehicular networks to enable the vehicles to exchange data content or cache the data for others while promoting the broadband services for vehicle users [9][10]. Therefore, exploring the benefits of CMC is replete with research significance.

Although the use of CMC is able to reduce energy consumption for a group of MTs when receiving multimedia data of common interested, the selected offloading MTs may consume more energy during local data chunk dissemination during a certain time duration. Therefore, due to the selfish nature of the MTs, how to stimulate and bootstrap the users to join the cloud and offload data for others are of research importance. The most common concerns involve the social benefits, such as awards or payment reduction. Meanwhile, intuitively and interestingly, the emerging simultaneous wireless information and power transfer (SWIPT) technique [11] [12] provides another potential solution from the technological domain. Through SWIPT, the receiver not only receives data from the transmitter, but can also "recycle" the transmit power to prolong battery lifetime. Nowadays, electromagnetic wave is almost omnipresent. So enabling SWIPT is full of potential, especially for MTs experiencing difficulties accessing other energy sources such as solar and wind. In [13], the authors propose a receiver architecture which can split the received power into two power streams to facilitate the SWIPT. In [14], different subcarrier and power allocation algorithms are proposed for the multiuser OFDM systems with SWIPT. For a multi-input multi-output (MIMO) system with SWIPT receivers, the authors of [16] present an optimization scheme to design the beamforming strategies. Similarly, in the context of multiple antenna transmission with wireless power transfer, there has been some work, e.g. [17],[18], dedicated to the development of beamforming design. In [17], the authors propose a joint beamforming algorithm for a multiuser SWIPT system with multiple user (MU) MIMO transmission with the objective to maximize the harvested energy. The authors of [18] also study a similar model and propose the algorithms to maximize the weighted sum-power transferred to all energy receivers.

It is easy to see that previous works do not explore resource allocation and beamforming design for such a wireless power transfer enabled content distribution structure. In addition, investigating the energy efficiency of CMC needs more effort. In this work, we aim to study resource allocation and data offloading schemes for wireless power transfer (WPT) enabled collaborative mobile clouds (WeCMC) with the objective to maximize the energy efficiency of the considered system. By "wireless power transfer enabled", we mean that introducing WPT into the CMC is able to stimulate users to join the cloud, and enable the CMC to be realized. With WPT, the MTs inside the CMC can be charged by the BS via an RF signal, which brings another thought over the economic or social aspects. In the traditional service, each MT has to download the whole content on its own, which leads to significant energy consumption of the batteries, especially if the cellular data rates are relatively low. In the proposed WeCMC model, all the MTs can be categorized as data offloading receiver (DORs) and energy harvesting receivers (EHRs) according to their rules in the transmission. When BS transmitting one data trunk, the DORs can receive/offload the transmitted data. Meanwhile, the other MTs will act as EHRs that can harvest energy from the BS. Then, after the transmission of BS, the DORs can deliver the data to the EHRs who do not receive data from the BS. Previous work on the related subject mainly focuses on the user-set formulation or energy efficiency investigations [7] [15]. How to allocate the limited radio resources, such as subchannels or transmit power, is often not considered. Moreover, how to select users to offload data and how to design beamforming for both information and energy transfer in the context of multiple-antenna transmitter also needs to be investigated. Intuitively, energy optimization in the considered system introduces two contradict objectives: energy harvesting maximization and transmission energy minimization, which makes the problem more complicated. In this work, we are going to address these problems. Compared to previous work, our main contributions can be summarized as follows:

- One of the main focus of this work is to propose a user scheduling scheme that can select the optimal number of MTs to obtain the energy consumption minimization. As far as the SWIPT features for WeCMC are concerned, how to schedule the proper MTs to offload data and transmit to other MTs is of considerable research importance. With the objective to obtain energy efficiency for the content distribution in WeCMC, the selected MTs are able to minimize the energy cost for the overall system and maximize the harvested energy from wireless power transfer. The proposed schemes are evaluated by extensive simulations, and a corresponding analysis is provided.
- Eventually, better channel conditions and higher transmit power of the BS can bring more energy for wireless power transfer. Therefore, which set of subchannels and how much transmit power should be used so that the sum of the consumed energy and harvested energy can be minimized calls for constant consideration. We also propose an algorithm that can properly assign the subchannels for the transmission between the BS and WeCMC, and the transmission within WeCMC. Moreover, beamforming design for the multiple antenna BS and power allocation for MTs have been addressed so that the transmit power consumption can be minimized. In particular, we advocate the alternating direction method of multipliers (ADMM) algorithm and proximal operator algorithm to solve the formulated beamforming design problem so that energy consumption can be minimized. Our simulation studies have shown that with proper resource allocation

algorithms, the WeCMC can obtain significant energy efficiency in its performance and remarkably reduce energy consumption of MTs for receiving content. A more detailed discussion, together with an in-depth analysis as well as future research directions are presented.

The rest of this paper is organized as follows. Section II describes the collaborative mobile cloud system model and presents the energy consumption models of WeCMC. In Section III, the optimization problem is formulated, followed by the energy efficient solution in Section IV. We demonstrate the benefits of our proposed algorithm in Section V through simulation studies. We finally conclude this work in Section VI.

II. WeCMC System Description

In the considered system, there are one BS and M MTs who are interested in downloading from the BS. The MTs are able to decode information and harvest energy from the received radio signals. We consider a case where the BS is equipped with $N_T > 1$ antennas and all the MTs are equipped with a single antenna. We consider there is a total of N subchannels. Moreover, we assume the channel follows quasi-static block fading and the BS can accurately obtain the channel status information by the feedback from the MTs.

Fig. 1 depicts the transmission process of WeCMC compared to conventional transmission, e.g., unicasting/multicasting. In Fig. 1, the WeCMC consists of three MTs. As a simple example, we divide the overall data stream into 3 data chunks. In a conventional setup, the radio interface of a MT (e.g. stand-alone MT) has to remain active for the whole duration of reception. As a result, high energy consumption can be induced, as the required RF and baseband processing need to remain active during data reception. In the CMC, the BS can distribute various data chunks to different MTs, and MTs can then exchange/share the offloaded parts with other members via D2D transmission. A detailed example of the transmission procedure is presented in Fig. 2. In the case illustrated Fig. 2, one MT is selected each time to decode and transmit data to other MTs. For example, for the first data segment the BS can distribute it the second WeCMC MTs, and the MT can then transmit the received parts with other MTs by utilizing the SR transmission among MTs. Thus, the reception duration can be considerably reduced compared to the conventional transmission given that SR usually has a better data rate, due to, e.g., the closer distance [7]. However, it is worth noting that in order to share the offloaded data, additional communication overheads are induced, including transmit power of D2D transmitters and transmit/receive durations [7]. Consequently, the inherent energy efficiency improvement requires careful algorithm design [21].

To concentrate on data offloading and resource allocation proposals, we do not assume any particular type of wireless power transfer receivers. The considered MT in this work consists of an energy harvesting unit for power transfer and a conventional signal processing core unit for data offloading and decoding, respectively. Moreover, for conventional signal processing, we separate receiver architecture into the RF unit and baseband unit. In the following section, the energy consumption models will be provided. Prior to the introduction of the energy consumption models, several indicators are defined. First, the user selection indicator ρ_k is defined as follows,

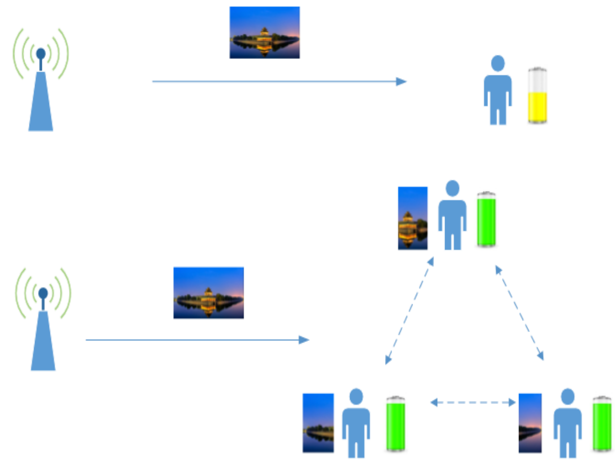

Fig. 1. Collaborative mobile clouds

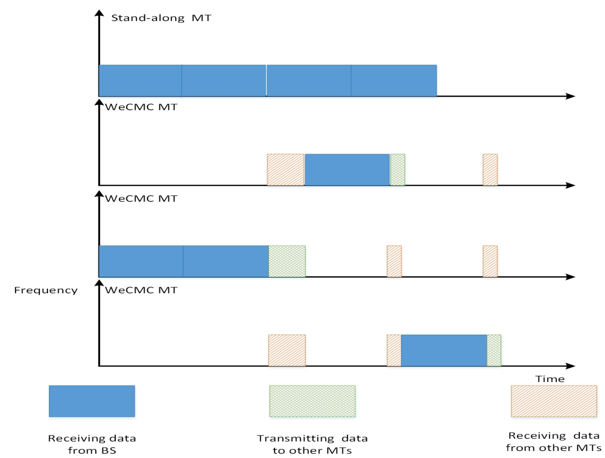

Fig. 2. Transmission process

$$\rho_k = \begin{cases} 1, & \text{if } k \text{ is chosen for receiving data from a BS,} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

In addition, we also define β as the indicator on whether a certain subchannel is assigned to MTs $\mathcal{K}$, e.g.,

$$\beta_{s,\mathcal{K},i} = \begin{cases} 1, & \text{if subchannel } i \text{ is used for downlink for set } \mathcal{K}, \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

and

$$\tau_{\mathcal{K},j} = \begin{cases} 1, & \text{if subchannel } j \text{ is assigned to deliver data for set } \mathcal{K}, \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

In addition to the definition of indicators, some key notations and variables are presented in Table II.

TABLE I
NOTATION

Notation	Meaning
M	number of MTs;
N	number of subchannels;
ρ_k	indicator whether MT k is scheduled as a DOR;
$\mathcal{K}$	set of the DORs;
$\beta_{s,\mathcal{K},i}$	indicator on whether subchannel i is allocated for transmission from BS to $\mathcal{K}$;
$\tau_{\mathcal{K},j}$	indicator on whether subchannel j is allocated for transmission from $\mathcal{K}$ to other MTs;
$\boldsymbol{\omega}_i$	information beamforming vector on subchannel i;
$\boldsymbol{\upsilon}_{b,i}$	energy beamforming vector on subchannel i;
$\mathbf{h}_{s,k,i}$	channel coefficient from the BS to MT k on subchannel i;
$R^c_{s,k,i}$	throughput of the cellular link from the BS to MT k on subchannel i;
$R^c_{s,\mathcal{K},i}$	throughput of the cellular link from the BS to $\mathcal{K}$ DORs on subchannel i;
$R^d_{\mathcal{K},j}$	throughput of the D2D link from $\mathcal{K}$ DORs to others on subchannel j;
E^{ctx}_s	transmit energy consumption of the BS on subchannel i ;
$E_{\mathcal{K},i,j}$	total energy consumption of DORs in $\mathcal{K}$ using subchannel i and subchannel j ;
$E^{drx}_{n,j}$	receving energy consumption of EHR n for receiving from DORs on subchannel j ;

A. Channel Model

We assume the receivers have both data offloading and energy harvesting functionalities but can only perform one of these due to hardware limitations. In the following, we refer to the receivers which perform data offloading functionality as data offloading receivers (DORs) and energy harvesting MTs as energy harvesting receivers (EHRs). The roles of the DORs and EHRs here are presented as follows,

DOR: The DOR is responsible for receiving from the BS for data offloading. After receiving from the BS, the DOR will distribute the data to other MTs inside WeCMC.

EHR: The EHR is a MT that is not selected to offload the data. In stead of receiving data from the BS, the EHR can obtain energy transfer from the BS and charge the battery correspondingly.

For the cellular link transmission between the BS and MTs, it is more efficient to use multicasting as the transmission mechanism and to consider the channel as a multiple-input-single-output (MISO) multicasting channel. By using multicasting, the BS can deliver the same data to different MTs with less spectrum. Without loss of generality, we consider the DORs with a dedicated information beam and other MTs with B energy beams. By denoting $\mathbf{s}$ as the transmit information signal for the DORs and θ as the energy carrying signal, the transmitted signal can be expressed as [18]

$$\chi = \boldsymbol{\omega}_i \boldsymbol{\alpha} + \sum_{b=1}^{B} \boldsymbol{\upsilon}_{b,i} \boldsymbol{\theta}, \tag{4}$$

where $\boldsymbol{\omega}_i$ and $\boldsymbol{\upsilon}_{b,i}$ are the information beamforming vector for the DORs and the energy beamforming vector on subchannel i, respectively. The $\boldsymbol{\alpha}$ is the source information signal. For the energy signal $\boldsymbol{\theta}$, it carries no information. Moreover, it is also reasonable to assume that θ is known to the DORs. Therefore, the DORs can successfully decode $\mathbf{u}$ and then ignore it. Without loss of generality, we consider that the information signal and energy signal both have unit variance. $\mathbf{h_{s,k,i}} \in \mathbb{C}^{N_T \times 1}$ is the channel coefficient from the source BS s to MT k on subchannel i. So the received signal at MT k is

$$y_{s,k,i} = \mathbf{h}^H_{s,k,i} \boldsymbol{\chi} + n_{s,k,i}, \tag{5}$$

where $n_{s,k,i}$ is the additive Gaussian noise which follows $\mathcal{N}(0, \sigma_z^2)$. It is worth noticing that $\mathbf{h}_{s,k,i}$ represents the path loss, slow and fast fading effects. $\mathbf{h}^H_{s,k,i}$ is the conjugate transpose of $\mathbf{h}_{s,k,i}$. In the following, we will present the throughput of DOR and the energy harvesting model of EHR.

B. Data Offloading Receiver

Accordingly, for the selected DOR k, the data rate $R^c_{s,k,i}$ of cellular link from BS to k on subchannel i can be expressed as

$$R^c_{s,k,i} = \log_2 \left(1 + \frac{|\mathbf{h}^H_{s,k,i} \boldsymbol{\omega}_i|^2}{\sigma_z^2} \right). \tag{6}$$

We assume K DORs are selected for data assignment, and the set of selected DORs is $\mathcal{K}$. Then, for the selected K DORs, the data rate can be expressed as

$$R^c_{s,\mathcal{K},i} = \min_{k \in \mathcal{K}} \left\{ \beta_{s,\mathcal{K},i} \log_2 \left(1 + \frac{\rho_k |\mathbf{h}^H_{s,k,i} \boldsymbol{\omega}_i|^2}{\sigma_z^2} \right) \right\}. \tag{7}$$

After receiving from the BS, the K DORs distribute the data to the other MTs via multicasting. We refer to the transmission between the DORs and EHRs as the D2D link. On D2D link, we assume no additional spectrum is used comparing with the cellular link. Thus, one subchannel is considered. The D2D communication within the WeCMC can be modeled as a virtual MISO multicasting channel if multiple DORs were selected and as a single-input-single-output (SISO) channel if only one DOR was selected. Therefore, the data rate of the D2D link on subchannel j is

$$R^d_{\mathcal{K},j} = \sum_{k \in \mathcal{K}} \rho_k \tau_{\mathcal{K},j} \log_2 \left(1 + \frac{p^{d_{tx}}_{k,j} |h_{k,j}|^2}{\sigma_z^2} \right), \tag{8}$$

where $p^{d_{tx}}_{k,j}$ is the multicasting power of DOR k on subchannel j and $h_{k,j}$ is the channel coefficient from the DOR $k \in \mathcal{K}$ to the MTs with worst channel gain. In addition, we also assume the noise of both links are the same.

C. Energy Harvesting Receiver

In practice, electromagnetic induction and electromagnetic radiation are able to transfer wireless power, and the receiver is able to recycle wireless power from the radio signal [12]. Meanwhile, due to the fact that the associated hardware circuit in the receivers might differ, the corresponding energy harvesting efficiency can be different as well. In the case of EHRs, no baseband processing is needed to harvest the carried energy through the beamforming vectors [13]. Based on the law of energy conservation, the harvested energy is proportional to the total received power. In addition, as the RF signal can carry both data and energy, the receiver can receive either data or energy in accordance of its own need. Thus, SWIPT can be realized in the same frequency band [13]. In this work, we consider that there is only one frequency band is used for the cellular link for both data transmission and wireless power transfer, i.e., same subchannel i is used for both DORs and EHRs.

Thus, in the presence of DOR k, the harvested energy of EHR n on subchannel i is given by

$$P^{EH}_{s,n,i} = \rho_k \beta_{s,\mathcal{K},i} \vartheta_n \Gamma_i \|\mathbf{h}_{s,n,i}\|^2, \tag{9}$$

where $\Gamma_i = \|\boldsymbol{\omega}_i\|^2 + \sum_{b=1}^{B} \|\boldsymbol{\upsilon}_{b,i}\|^2$ is the transmit power consumption and the conversion efficiency $0 < \vartheta_n \leq 1$.

D. Energy Consumption Model

1) Energy Consumption of the BS: The energy consumption of BS is given as [14][19]

$$E^{c_{tx}}_{s} = \frac{(\varepsilon \Gamma_i + p_b) S_T}{\sum_{i=1}^{N} R^c_{s,\mathcal{K},i}}, \tag{10}$$

where p_b is the BS operating power consumption which we consider to be constant. S_T is the amount of data to be transmitted. ε stands for the nonlinearity effect of power amplifier.

2) Tx and Rx Energy Consumption of CMC: The energy consumption for receiving data size S_T from the BS can be expressed as

$$E^{c_{rx}}_{s,k,i} = (p^{c_{rx}}_{s,k,i} + p_e) T^{c_{rx}}_{s,k,i} = \frac{(p_{rx} + p_e) S_T}{R^c_{s,\mathcal{K},i}}, \tag{11}$$

where $p^{c_{rx}}_{s,k,i}$ is the RF power consumption of k for receiving from the BS on subchannel i, and p_e is the electronic circuit power consumption of the baseband associated with transmission bandwidth. In this work, the energy consumption refers to the one when receiving and sending data on a certain subchannel. Thus, the baseband power consumption is considered together with RF Tx/Rx power consumption. $T^{c_{rx}}_{s,k,i} = \frac{S_T}{R^c_{s,\mathcal{K},i}}$ is the required time for receiving data S_T on cellular link subchannel i. Further, we can assume the receive RF power consumption is the same for both cellular and D2D links, and equal to p_{rx}. After receiving from the BS, DOR k is going to transmit its offloaded data to other MTs. There are two conventional ways to deliver data inside WeCMC, which are unicasting and multicasting. We have discussed the energy efficiency of using both two schemes in [21] where the multicasting showed superior energy efficiency performance over unicasting. Therefore, in this work, we only advocate multicasting as the transmission strategy inside WeCMC.

When the multicasting strategy is used, a DOR only needs to broadcast its data once to other MTs in CMC, with a data rate that can reach the MT with the worst channel condition. Accordingly, D2D communication within the WeCMC can be modeled as a virtual MISO channel. Thus, the transmit energy consumption is given as

$$E^{d_{tx}}_{k,j} = (\varepsilon p^{d_{tx}}_{k,j} + p_e) T^{S_{tx}}_{\mathcal{K},j} = \frac{(\varepsilon p^{d_{tx}}_{k,j} + p_e) S_T}{R^d_{\mathcal{K},j}}. \tag{12}$$

Therefore, the total energy consumption of WeCMC when using the MTs in $\mathcal{K}$ as the DORs can be expressed as follows:

$$E_{\mathcal{K},i,j} = \sum_{k \in \mathcal{K}} \rho_k (\sum_{i=1}^{N} \beta_{s,\mathcal{K},i} E^{c_{rx}}_{s,k,i} + \sum_{j=1}^{N} \tau_{\mathcal{K},j} E^{d_{tx}}_{k,j}) + \sum_{n, n \notin \mathcal{K}}^{M} \sum_{j=1}^{N} \tau_{\mathcal{K},j} E^{d_{rx}}_{n,j}. \tag{13}$$

$E_{\mathcal{K},i,j}$ is the energy consumption of the DORs in $\mathcal{K}$ when subchannel i is assigned for receiving from the BS and subchannel j for broadcasting its received data. $E^{d_{rx}}_{n,j}$ is the energy consumption of each EHR when receiving from the DORs on subchannel j, and it can be expressed as

$$E^{d_{rx}}_{n,j} = (p^{d_{rx}}_{n,j} + p_e) T^{d_{rx}}_{k,j} = \frac{(p_{rx} + p_e) S_T}{R^d_{\mathcal{K},j}}. \tag{14}$$

III. Problem Formulation

Intuitively, the long transmission time of a cellular link can increase the time for wireless power transfer, but at the cost of transmit energy consumption. Therefore, in order to minimize the energy consumption for a fixed amount of data, we formulate a joint optimization problem of beamforming design, user set selection, and subchannel and power allocation. The main focus of the considered problem is to minimize the overall energy consumption of WeCMC during each transmission interval. This is done through two contradictory objectives: maximization of the wireless harvested energy and minimization of the consumed transmission energy of both BS and MTs.

For each data segment transmission, we can formulate the optimization objective as

$$\mathcal{E}(\boldsymbol{\rho}, \boldsymbol{\beta}, \boldsymbol{\tau}, \boldsymbol{\omega}, \boldsymbol{\upsilon}, \mathbf{P}) = E^{c_{tx}}_{s} + E_{\mathcal{K},i,j} - \sum_{n, n \notin \mathcal{K}}^{M} Q_{s,n,i}, \tag{15}$$

where N is the number of available subchannels and K is the total number of DORs. $\mathbf{P}$ is the power allocation policy for D2D communication inside WeCMC. $\boldsymbol{\rho} = \{\rho_k\}, \forall k$ and $\boldsymbol{\beta} = \{\beta_{s,\mathcal{K},i}\}$ and $\boldsymbol{\tau} = \{\tau_{\mathcal{K},j}\}$ are the user selection and subchannel allocation indicators. $\boldsymbol{\upsilon}$ and $\boldsymbol{\omega}$ are the beamforming design policy. $Q_{s,n,i}$ is the harvested energy and obversely $Q_{s,n,i} = P^H_{s,n,i} S_T / R^c_{s,\mathcal{K},i}$. Therefore, $\mathcal{E}(\boldsymbol{\rho}, \boldsymbol{\beta}, \boldsymbol{\tau}, \boldsymbol{\omega}, \boldsymbol{\upsilon}, \mathbf{P})$ stands for the overall energy consumption for the data amount

S_T transmission, i.e., the energy consumption of the BS and all the MTs. Note that mathematically $\mathcal{E}$ can take a negative value, while in practice $\mathcal{E}$ is always positive due to the fact that the transmit power consumption of the BS dominates. Therefore, the optimization problem (**P1**) can be formulated as

$$\min_{\boldsymbol{\rho},\boldsymbol{\beta},\boldsymbol{\tau},\boldsymbol{\omega},\boldsymbol{\upsilon}} \mathcal{E}(\boldsymbol{\rho},\boldsymbol{\beta},\boldsymbol{\tau},\boldsymbol{\omega},\boldsymbol{\upsilon},\mathbf{P}), \tag{16}$$

s.t.

$$\begin{aligned}
&C1: \sum_{i=1}^{N}\beta_{s,\mathcal{K},i}=1, \sum_{j=1}^{N}\tau_{\mathcal{K},j}=1,\\
&C2: R^{c}_{s,\mathcal{K},i}\geq R_{c,min},\\
&C3: R^{d}_{\mathcal{K},j}\geq R_{d,min},\\
&C4: \Gamma_i \leq p_{s,max},\\
&C5: p^{d_{tx}}_{k,j}\leq p_{k,max}.
\end{aligned} \tag{17}$$

Several constraints in (17) for the optimization problem (16) can ensure that the solution is feasible. The first constraint **C1** is to make sure that one subchannel is used for the cellular link and one for the D2D link. As the transmissions of the cellular link and D2D link are scheduled in different time slots, the subchannels used on different links can be same as no interference takes place. $R_{c,min}$ in **C2** and $R_{d,min}$ in **C3** are the required data rates for the cellular and D2D links, respectively. It is also worth noticing that the minimum data rate requirement for two links should be different and in general, $R_{d,min}$ is higher than $R_{c,min}$ to get energy efficiency as well as to minimize the delay. **C4** and **C5** ensure that the power allocation of the BS and DOR should not be higher than the maximum allowed transmit power.

It is worth noticing that (16) with constraints in (17) is a non-convex problem. Addressing such an integer programming non-convex optimization problem is recognized as NP-hard. An exhaustive search is needed to obtain the global optimum. This incurs a high computational cost, even for small M and N. In order to make the problem tractable and to simplify the problem, we transform the objective function and approximate the transformed objective function.

IV. Energy Efficiency Optimization of WeCMC

In this section, we present an energy efficiency optimization algorithm for the WeCMC. In particular, we first transform the formulated fractional programming problem into a subtractive form. Then, by relaxing the constraints on subchannel allocation and assuming that subchannel allocation is done, the beamforming vector can be optimized by using the alternating direction method of multipliers (ADMM) scheme. Consequently, subchannel allocation and user scheduling schemes are presented. First, we introduce the problem transformation and beamforming design.

A. Beamforming Design

1) Problem Transformation: Given that the DORs are selected, we can reform objective $\mathcal{E}$ as a function of $\{\boldsymbol{\beta},\boldsymbol{\tau},\boldsymbol{\omega},\boldsymbol{\upsilon},\mathbf{P}\}$. Substituting (9), (10) and (13) into (15), we can obtain (18), where $p_c = p_b + p_{rx} + p_e$ and $\Gamma_i = \|\boldsymbol{\omega}_i\|^2 + \sum_{b=1}^{B}\|\boldsymbol{\upsilon}_{b,i}\|^2$. One may notice that to obtain a resource allocation policy, one should find the optimal solution to minimize $\mathcal{E}(\boldsymbol{\beta},\boldsymbol{\tau},\boldsymbol{\omega},\boldsymbol{\upsilon},\mathbf{P})$, which is

$$\mathcal{E}(\boldsymbol{\beta},\boldsymbol{\tau},\boldsymbol{\omega},\boldsymbol{\upsilon},\mathbf{P}) = \mathcal{E}_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon}) + \mathcal{E}_d(\boldsymbol{\tau},\mathbf{P}), \tag{19}$$

where $\mathcal{E}_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon}) = \frac{U_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon})}{R_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon})}$ and $\mathcal{E}_d(\boldsymbol{\tau},\mathbf{P}) = \frac{U_d(\boldsymbol{\tau},\mathbf{P})}{R_d(\boldsymbol{\tau},\mathbf{P})}$. From (19), it can be seen that the beamforming design and power allocation for the BS and scheduled DORs are separated. In other words, we can obtain the optimal beamforming vector, and subchannel and power allocation by addressing $\mathcal{E}_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon})$ and $\mathcal{E}_d(\boldsymbol{\tau},\mathbf{P})$ individually given that certain DORs are selected. For the sake of presentation simplicity, we introduce a nonlinear programming method for solving $\mathcal{E}_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon})$ which is derived from [23].

The global optimal solution q_c^* for minimizing $\mathcal{E}_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon})$ can be expressed as

$$q_c^* = \mathcal{E}_c(\boldsymbol{\beta}^*,\boldsymbol{\omega}^*,\boldsymbol{\upsilon}^*) = \min_{\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon}} \frac{U_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon})}{R_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon})}. \tag{20}$$

where $\boldsymbol{\beta}^*,\boldsymbol{\omega}^*,\boldsymbol{\upsilon}^*$ are the optimal solutions for $\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon}$, respectively.

Theorem 1. *q_c can reach its optimal value if and only if*

$$\min_{\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon}} U_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon}) - q_c R_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon}) = 0. \tag{21}$$

Proof. The proof is given in Appendix A. □

Theorem 1 presents the necessary and sufficient condition w.r.t. the optimal solution. Particularly, for the considered optimization problem with an objective function in the fractional form, there exists an equivalent optimization problem with an objective function in the subtractive form, i.e., $U_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon}) - q_c^* R_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon})$, and both formulations result in the same resource allocation solutions. In order to obtain the q_c^*, the iterative algorithm with guaranteed convergence in [23] can be applied and it can be found in Alg. 1. The proof of convergence can be found in Appendix B.

Algorithm 1 Iterative Algorithm for Obtaining q_c^*

Set maximum tolerance δ;
while (not convergence) **do**
  Solve the problem (22) for a given q_c and obtain subchannel allocation and beamforming design $\{\boldsymbol{\beta}',\boldsymbol{\omega}',\boldsymbol{\upsilon}'\}$;
  if $U_c(\boldsymbol{\beta}',\boldsymbol{\omega}',\boldsymbol{\upsilon}') - q_c R_c(\boldsymbol{\beta}',\boldsymbol{\omega}',\boldsymbol{\upsilon}') \leq \delta$ **then**
    Convergence = true;
    return $\{\boldsymbol{\beta}^*,\boldsymbol{\omega}^*,\boldsymbol{\upsilon}^*\} = \{\boldsymbol{\beta}',\boldsymbol{\omega}',\boldsymbol{\upsilon}'\}$ and obtain q_c^* by (20);
  else
    Convergence = false;
    return Obtain $q_c = \frac{U_c(\boldsymbol{\beta}',\boldsymbol{\omega}',\boldsymbol{\upsilon}')}{R_c(\boldsymbol{\beta}',\boldsymbol{\omega}',\boldsymbol{\upsilon}')}$;
  end if
end while

$$\mathcal{E}(\boldsymbol{\beta},\boldsymbol{\tau},\boldsymbol{\omega},\boldsymbol{\upsilon},\mathbf{P}) = \frac{\overbrace{S_T\left(\sum_{i=1}^{N}\beta_{s,\mathcal{K},i}\Gamma_i + p_c - \sum_{i=1}^{N}\sum_{n,n\notin\mathcal{K}}^{M}\beta_{s,\mathcal{K},i}\vartheta_n\Gamma_i\|\mathbf{h}_{s,n,i}\|^2\right)}^{U_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon})}}{\underbrace{\sum_{i=1}^{N}\beta_{s,\mathcal{K},i}R^c_{s,\mathcal{K},i}}_{R_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon})}} + \frac{\overbrace{S_T\sum_{j=1}^{N}\tau_{\mathcal{K},j}(\sum_{k}^{K}p^{d_{tx}}_{k,j} + \sum_{n\notin\mathcal{K}}^{M}p_{rx} + \sum_{n}^{M}p_e)}^{U_d(\boldsymbol{\tau},\mathbf{P})}}{\underbrace{\sum_{j=1}^{N}\tau_{\mathcal{K},j}R^d_{\mathcal{K},j}}_{R_d(\boldsymbol{\tau},\mathbf{P})}}. \tag{18}$$

During the iteration, in order to achieve q_c^*, we need to address the following problem (**P2**) with q_c:

$$\min_{\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon}} U_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon}) - q_c R_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon}), \tag{22}$$

s.t.

$$\begin{aligned} &\sum_{i=1}^{N}\beta_{s,\mathcal{K},i} = 1,\\ &R^c_{s,\mathcal{K},i} \geq R_{c,min},\\ &\Gamma_i \leq P_{s,max}. \end{aligned} \tag{23}$$

In (**P2**), we can see that addressing the objective function involves finding $\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon}$, which can be represented as

$$\begin{aligned} &\min_{\boldsymbol{\omega},\boldsymbol{\upsilon}_b} S_T(\sum_{i=1}^{N}\beta_{s,\mathcal{K},i}\Gamma_i + p_c - \sum_{i=1}^{N}\sum_{n,n\neq k}^{M}\beta_{s,\mathcal{K},i}\vartheta_n\Gamma_i\|\mathbf{h}_{s,n,i}\|^2) - \\ &\quad q_c\sum_{i=1}^{N}\beta_{s,\mathcal{K},i}\log_2\left(1+\frac{|\mathbf{h}^H_{s,k,i}\boldsymbol{\omega}_i|^2}{\sigma_z^2}\right), \end{aligned} \tag{24}$$

With the assumption that the subchannel allocation is done, the focus, in turn, is to design the beamforming as well as power allocation policy. We can apply the nonlinear fractional programming method to solve the formulated problem [23] of beamforming, power allocation and subchannel allocation in the followings.

Basically, such problem is still a non-convex optimization problem due to the involved integer programming. Tackling the mix convex and combinatorial optimization problem and obtaining a global optimal solution result in a prohibitively high complexity. Another solution which can balance the computational complexity and optimality can be obtained when addressing such a problem in the dual domain. As discussed in [24], in the considered multi-carrier systems the duality gap of such a non-convex resource allocation problem satisfying the time-sharing condition is negligible as the number of subcarriers becomes sufficiently large e.g., 32 or 64. To address this problem, we relax $\beta_{s,\mathcal{K},i}$ to be $[0,1]$ instead of a Boolean. Then, $\beta_{s,\mathcal{K},i}$ can be interpreted as a time sharing factor for utilizing subchannel. Since our optimization problem satisfies the time-sharing condition, the considered problem can be solved accordingly. Prior to finding the solutions for subchannel allocation, we address the beamforming design problem. Note that the same idea can be used for addressing $\tau^*_{\mathcal{K},j}$ and $P^{d_{tx}}_{k,j}{}^*$.

2) Proposed Solutions: We first solve the beamforming problem of the cellular link for a given value of q_c and a fixed subchannel allocation. To address the formulated problem, we let

$$\|\boldsymbol{\omega}_i\|^2 + \sum_{b=1}^{B}\|\boldsymbol{\upsilon}_{b,i}\|^2 = \|I_\omega\boldsymbol{x}\|^2 + \|I_\upsilon\boldsymbol{x}\|^2 = \|\boldsymbol{x}\|^2, \tag{25}$$

where $\boldsymbol{x} = [\boldsymbol{\omega},\boldsymbol{\upsilon}_1,\boldsymbol{\upsilon}_2,...,\boldsymbol{\upsilon}_b]$ and

$$I_\omega = \begin{bmatrix} 1 & 0 & \dots & \dots & \dots & 0\\ 0 & \ddots & 0 & \dots & \dots & \vdots\\ \vdots & 0 & 1 & 0 & \dots & \vdots\\ \vdots & \dots & \dots & 0 & \dots & \vdots\\ \vdots & \dots & \dots & \dots & \ddots & \vdots\\ \vdots & \dots & \dots & \dots & \dots & 0 \end{bmatrix},$$

$$I_\upsilon = \begin{bmatrix} 0 & \dots & \dots & \dots & \dots & 0\\ \vdots & \ddots & \dots & \dots & \dots & \vdots\\ \vdots & \dots & 0 & \dots & \dots & \vdots\\ \vdots & \dots & 0 & 1 & 0 & \vdots\\ \vdots & \dots & \dots & 0 & \ddots & 0\\ \vdots & \dots & \dots & \dots & 0 & 1 \end{bmatrix}.$$

Moreover, we can also reform $|\mathbf{h}^H_{s,k,i}\boldsymbol{\omega}|^2$ as follows,

$$|\mathbf{h}'^H_{s,k,i}\boldsymbol{\omega}_i|^2 = |\mathbf{h}^H_{s,k,i}\boldsymbol{\omega}_i|^2, \tag{26}$$

where $\mathbf{h}'^H_{s,k,i} = [\mathbf{h}^H_{s,k,i}, 0, \dots, 0]$. Due to the fact that the logarithmic function in (24) is a monotone, increasing, and positive function, addressing (24) equals to solving the following problem (**P3**),

$$\min_{\boldsymbol{x}} f(\boldsymbol{x}) = S_T(\|\boldsymbol{x}\|^2 + p_c - \sum_{n,n\neq k}\vartheta_n\|\boldsymbol{x}\|^2\|\mathbf{h}_{s,n,i}\|^2) - q_c\varpi(\boldsymbol{x}), \tag{27}$$

s.t.

$$\begin{aligned}&\varpi(\boldsymbol{x}) \geq \gamma_{c,min},\\&\|\boldsymbol{x}\|^2 \leq P_{s,max},\end{aligned} \tag{28}$$

where $\gamma_{c,min}$ is the SNR for providing $R_{c,min}$ and $\varpi(\boldsymbol{x}) = \boldsymbol{x}^T(\mathbf{h}'^{H}_{s,k,i})^T\mathbf{h}'^{H}_{s,k,i}\boldsymbol{x}/\sigma_z^2$.

To address the formulated problem, we advocate an algorithm based on the alternating direction method of multipliers (ADMM) [25]. We can reformulate the problem in (27) as a standard ADMM form,

$$\min_{\boldsymbol{x},\boldsymbol{z}} \quad f(\boldsymbol{x}) + g(\boldsymbol{z}) \quad \textbf{s.t.} \quad \boldsymbol{x} - \boldsymbol{z} = 0, \tag{29}$$

where $g(\boldsymbol{z})$ is the indicator function of set $\mathcal{C}$,

$$\mathcal{C} = \{\boldsymbol{x}|\varpi(\boldsymbol{x}) \geq \gamma_{c,min}\} \cap \{\boldsymbol{x}|\|\boldsymbol{x}\|^2 \leq P_{s,max}\}.$$

The augmented Lagrangian of problem (29) can be given as,

$$\mathcal{L}_\rho(\boldsymbol{x},\boldsymbol{z},\boldsymbol{u}) = f(\boldsymbol{x}) + g(\boldsymbol{z}) + \frac{\rho}{2}\|\boldsymbol{x} - \boldsymbol{z} + \boldsymbol{u}\|_2^2, \tag{30}$$

where ρ is the penalty parameter and $\boldsymbol{u}$ is the scaled dual variable. Then the ADMM decomposition technique can be used to solve the problem in an iterative procedure in (29). Specifically, at the l-th iteration, Specifically, at the l-th iteration, the primal variables $\boldsymbol{x}$ and $\boldsymbol{z}$, and the dual variable $\boldsymbol{u}$ are updated sequentially as

$$\begin{aligned}&\boldsymbol{x}^{l+1} := \arg\min_{\boldsymbol{x}}(f(\boldsymbol{x} + (\rho/2))\|\boldsymbol{x} - \boldsymbol{z}^l + \boldsymbol{u}^l\|_2^2),\\&\boldsymbol{z}^{l+1} := \arg\min_{\boldsymbol{z}}(g(\boldsymbol{z} + (\rho/2)\|\boldsymbol{z} - \boldsymbol{x}^{l+1} - \boldsymbol{u}^l\|_2^2),\\&\boldsymbol{u}^{l+1} := \boldsymbol{u}^l + \boldsymbol{x}^{l+1} - \boldsymbol{z}^{l+1}.\end{aligned} \tag{31}$$

Algorithm 2 Proposed Algorithm for Beamforming

1: Initialize $\boldsymbol{x}^0$, $\boldsymbol{z}^0$, $\boldsymbol{u}^0$ and ρ;
2: **for** l=0,1,..., **do**
3: $\quad \boldsymbol{x}^{l+1} = \arg\min_{\boldsymbol{x}}(f(\boldsymbol{x}) + (\rho/2)\|\boldsymbol{x} - \boldsymbol{z}^l + \boldsymbol{u}^l\|_2^2)$;
4: $\quad \boldsymbol{z}^{l+1} = \arg\min_{\boldsymbol{z}}(g(\boldsymbol{z}) + (\rho/2)\|\boldsymbol{z} - \boldsymbol{x}^{l+1} - \boldsymbol{u}^l\|_2^2)$;
5: $\quad \boldsymbol{u}^{l+1} = \boldsymbol{u}^l + \boldsymbol{x}^{l+1} - \boldsymbol{z}^{l+1}$;
6: **end for**

The iterative scheme is illustrated in Alg. 2, which illustrates a scaled form ADMM with applications to our problem. The algorithm consists of an $\boldsymbol{x}$-minimization step, a $\boldsymbol{z}$-minimization step, and a dual variable update for $\boldsymbol{u}$. We update the primal variables $\boldsymbol{x}$ and $\boldsymbol{z}$ in an alternating or sequential fashion, which accounts for the term alternating direction. This is different from the method of multipliers, in which the augmented Lagrangian is minimized jointly with respect to the two primal variables $\boldsymbol{x}$ and $\boldsymbol{z}$. In order to separate the minimization over $\boldsymbol{x}$ and $\boldsymbol{z}$, $f(\cdot)$ and $g(\cdot)$ have to be separable, which is satisfied in our scenario. In this way, ADMM can have both the decomposability of dual ascent and the superior convergence properties of the method of multipliers, and we can easily solve our problem formulated in equations (27) and (28).

In Alg. 2, the proximal algorithm can be used for each iteration. The right hand side of the iterations for $\boldsymbol{x}^{l+1}$ and $\boldsymbol{z}^{l+1}$ can be denoted as the following proximal operators [26],

$$\begin{aligned}&\boldsymbol{x}^{l+1} = \textbf{prox}_{\frac{1}{\rho}f}(\boldsymbol{z}^l - \boldsymbol{u}^l),\\&\boldsymbol{z}^{l+1} = \textbf{prox}_{\frac{1}{\rho}g}(\boldsymbol{x}^{l+1} + \boldsymbol{u}^l).\end{aligned} \tag{32}$$

Take $\textbf{prox}_{\frac{1}{\rho}f}$ as an example, it is related to the subdifferential operator ∂f as follows,

$$\textbf{prox}_{\frac{1}{\rho}f} = (I + \frac{1}{\rho}\partial f)^{-1}, \tag{33}$$

where $(I + \frac{1}{\rho}\partial f)^{-1}$, known as the resolvent of the operator ∂f, is point-to-point mapping. So the above two proximal operators are equivalent to their corresponding resolvents of the subdifferential operators, and can be solved easily in each iteration in Alg. 2. Thus, we can address the beamforming vectors accordingly.

B. Subchannel Allocation

As we are able to relax $\beta_{s,\mathcal{K},i}$ to be $[0,1]$ instead of a Boolean, $\beta_{s,\mathcal{K},i}$ can be interpreted as a time sharing factor for utilizing subchannel. In order to obtain the optimal subchannel allocation $\beta^*_{s,\mathcal{K},i}$, we can apply the Karush-Kuhn-Tucker (KKT) conditions to the **P2**, and then obtain the subchannel allocation policy as follows

$$\beta^*_{s,\mathcal{K},i} = \begin{cases}1, & \text{if } i = \arg\max_d \Theta_d,\\0, & \text{otherwise},\end{cases} \tag{34}$$

where

$$\begin{aligned}\Theta_i =\ & S_T(\Gamma_i + p_c - \sum_{n\neq k}\vartheta_k\Gamma_i\|h_{s,n,i}\|^2) - q_c\\&+ \left(1 + \log_2(1 + \frac{|\mathbf{h}^H_{s,k,i}\boldsymbol{\omega}|^2}{\sigma_z^2}) - \frac{|\mathbf{h}^H_{s,k,i}\boldsymbol{\omega}|^2/\ln 2}{\sigma_z^2 + \Gamma_i|\mathbf{h}^H_{s,k,i}\boldsymbol{\omega}_i|^2}\right).\end{aligned} \tag{35}$$

Since the problem (22) is a convex optimization problem, it is guaranteed that the iteration converges to the primal optimal solution. Combining the proposed algorithm for obtaining q_c^*, the details of the subchannel and beamforming policies are presented in Alg. 3. Given a q_c, the beamforming problem can be addressed by solving (**P3**) and subchannel allocation can be solved by (34). Then, with the solution of beamforming and subchannel allocation, optimal q_c can be obtained.

We have presented the scheme on how to address the minimization of $\mathcal{E}_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{v})$. The similar procedure can be applied to obtain the optimal solution of minimizing $\mathcal{E}_d(\boldsymbol{\tau},\mathbf{P})$. Then we are able to obtain the solution set of (16) when considering the DORs are selected.

C. User Scheduling Scheme

For the user scheduling problem, the goal is to select MTs to act as DORs when the BS is transmitting a data segment and as the data transmitter forming a virtual MISO when delivering data to other MTs after receiving from the BS. Therefore,

Algorithm 3 Subchannel Allocation and Beamforming Design

1) Initialize q_c,$\boldsymbol{\omega}$,$\boldsymbol{\upsilon}$ and dual variables; Define δ as a small positive number;

while (Not Convergence) **do**
  Update dual variables.
  Solve the problem (34) for a given q_c and obtain subchannel allocation;
  Solve the problem (**P3**) via Alg. 2.
  if $U_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon}) - q_c R_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon}) > \delta$ **then**
    Set $q_c = \frac{U_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon})}{R_c(\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\upsilon})}$,
    Convergence = false,
  else
    Convergence = true,
    return $\boldsymbol{\omega}^* = \boldsymbol{\omega}$,$\boldsymbol{\upsilon}^* = \boldsymbol{\upsilon}$, $\beta^*_{s,\mathcal{K},i} = \beta_{s,\mathcal{K},i}$ and $q_c^* = q_c$,
  end if
end while
return Obtain subchannel allocation and beamforming vectors.

with the assumption that subchannel, beamforming and power allocations have been done, the goal is to find proper MTs that can achieve the best energy efficiency performance for both cellular multicasting link and the D2D multicasting link. When subchannel and power allocations are done, the objective function can be reformed as,

$$\min \mathcal{E}(\boldsymbol{\rho}) = \frac{U_c(\boldsymbol{\rho})}{R_c(\boldsymbol{\rho})} + \frac{U_d(\boldsymbol{\rho})}{R_d(\boldsymbol{\rho})}, \tag{36}$$

where

$$U_c(\boldsymbol{\rho}) = \rho_k S_T(\Gamma_i + p_c - \sum_{n, n\notin\mathcal{K}} \vartheta_n \Gamma_i \|\boldsymbol{h}_{s,n,i}\|^2), \tag{37}$$

$$U_d(\boldsymbol{\rho}) = S_T(\sum_k^K \rho_k p_{k,j}^{d_{tx}} + \sum_{n\notin\mathcal{K}} p_{rx} + \sum_n^M p_e), \tag{38}$$

$$\begin{aligned} R_c(\boldsymbol{\rho}) &= \min_{k\in\mathcal{K}} \left\{ \log_2\left(1 + \frac{\rho_k |\mathbf{h}_{s,k,i}^H \boldsymbol{\omega}|^2}{\sigma_z^2}\right)\right\}. \\ R_d(\boldsymbol{\rho}) &= \sum_{k\in\mathcal{K}} \rho_k \log_2\left(1 + \frac{p_{k,j}^{d_{tx}} |h_{k,j}|^2}{\sigma_z^2}\right). \end{aligned} \tag{39}$$

The reformed problem (36) is also subject to the constraints in (17). Therefore, the proposed algorithm should select K DORs that can minimize the energy consumption during transmission process. We can obtain the user scheduling criteria as,

$$\rho_k^* = \begin{cases} 1, & \text{if } k = \arg\min_a \Phi_a, \\ 0, & \text{otherwise}, \end{cases} \tag{40}$$

where

$$\Phi_a = \frac{U_c(\rho_a)}{R_1(\rho_a)} + \frac{U_d(\rho_a)}{R_2(\rho_a)}. \tag{41}$$

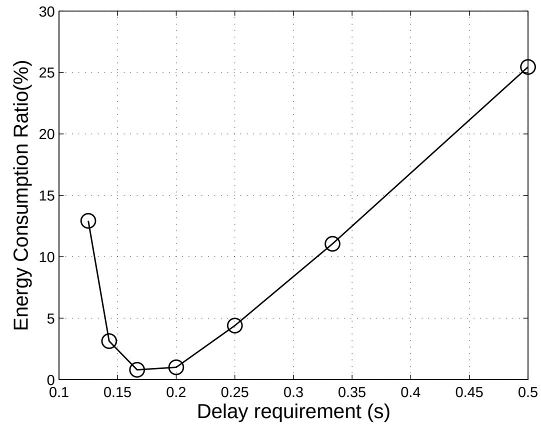

Fig. 3. Energy-delay Tradeoff

V. Performance Evaluation

A. Simulation Setting

For the cellular link, we use the Stanford University SUI-3 channel model and modify it to include multipath effects with 2GHz central frequency. We choose the number of subchannels N to be 64, so that the duality gap can be ignored [24]. Flat quasi-static fading channels are adopted, hence the channel coefficients are assumed to be constant during a complete data transmission, and can vary from one to another independently. For the D2D link, the path loss follows the IEEE 802.11ac standards with 5GHz central frequency. Noise variance is assumed 1 for simplicity.

In practice, the baseband power P_e and P_b are generally not constant and their values should depend on the circuit design. However, this is out of the scope of this work, and we assume they are fixed and the values are according to [15]. We also assume that $P_{s,max} = 46dBm$ and $P_{k,max} = 23dBm$ unless further specified. For simplicity, the conversion efficiency is assumed as $\vartheta_k = 0.5, \forall k$ and $\varepsilon = 0.2$. To illustrate the energy saving performance, we compare our resource allocation scheme with pure multicasting transmission, that is, the reference energy consumption is the one of which the BS uses to multicast all data to every MT. We consider the BS to be about 500m away from MTs, which are randomly located in a $100 \times 100m^2$ square.

In order to illustrate the advantages of the proposed scheme, we also compare our scheme (PS) with random subchannel allocation (RSA) and random MT and subchannel allocation (RUS with RSA).

B. Simulation Results

First, we present our study on the tradeoff between delay requirement and energy consumption. We plot a figure of energy consumption performance by varying the delay requirement. For a simple illustration, in Fig. 3, we have the data amount of one trunk $S_T = 1$ bit, 20 MTs in WeCMC and $R_{c,min} = 1$ bps. We consider that the service delay is caused purely by the additional D2D link, i.e., the data rate of the cellular link is similar to the one of traditional multicasting. Then,

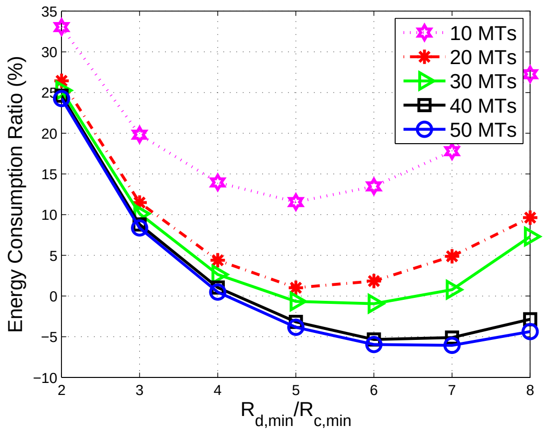

Fig. 4. Energy efficiency performance of MTs

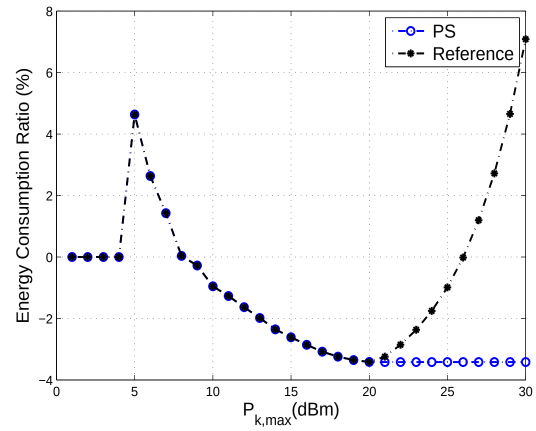

Fig. 5. Energy efficiency performance vs. $P_{k,max}$

we can vary the D2D link rate in order to satisfy different delay requirements. We can observe that when delay is low, the MTs need to use higher power to transmit to other MTs. Meanwhile, the time for transmitting is short, which results in a higher energy consumption. As the delay requirement becomes low, the energy consumption decreases as well due to lower transmit energy consumption. The trade-off point happens when delay is about 0.17s. After that, when delay increases, the energy consumption increases as well due to longer time for transmission.

In Fig. 4, we fix $R_{c,min} = 1$ bps/Hz and vary the value of $R_{d,min}$ to illustrate the energy saving benefits of WeCMC and the effectiveness of the WeCMC D2D link. The energy consumption ratio on the y-axis is given as

$$\mathrm{ECR} = \frac{\text{Energy consumption using WeCMC}}{\text{Energy consumption of traditional multicasting}} \times 100\%. \tag{42}$$

It can be noticed that, at first, when $R_{d,min}/R_{c,min}$ increases, the energy consumption of WeCMC is decreased. This is because when the time durations for transmitting and receiving are decreased, the energy consumption of MTs is also reduced. Since a higher data rate requires higher transmit power consumption, there is a trade-off between the energy consumption and the value of $R_{d,min}/R_{c,min}$. For example, for the case that WeCMC consists of 10 MTs, the best option for obtaining energy minimization is $R_{d,min}/R_{c,min} = 5$. The negative value on the y-axis of Fig. 4 implies that the harvested energy at MTs is higher than the consumed energy, which means that the WPT is appreciated for the MTs who are facing energy consumption problems but still like to download from the BS. Moreover, one can find that when WeCMC consists of more MTs, the energy saving potentials can be improved. In the following, we fix $R_{d,min}/R_{c,min} = 5$ to illustrate the energy saving performance.

Fig. 5 presents the energy consumption performance when there are 30 MTs inside WeCMC. We compare our proposed scheme with a reference scheme obtained by modifying the objective function (16) to the throughput maximization. We find that for $P_{k,max} < 5dBm$, $ECR = 0$ since the optimization problem is infeasible due to an insufficient power supply to satisfy the constraints on $R_{d,min}$. For a larger $P_{k,max}$, the energy consumption of the proposed algorithm first decreases and then approaches a constant due to a higher transmit power allowance becoming saturated. It can be observed that before certain point, the proposed scheme has the a performance similar to that of the throughput maximization scheme. It can also be noticed that the energy consumption of the reference scheme increases dramatically in the high transmit power regime. This is due to the fact that such scheme has a large power consumption for throughput maximization which causes low energy efficiency.

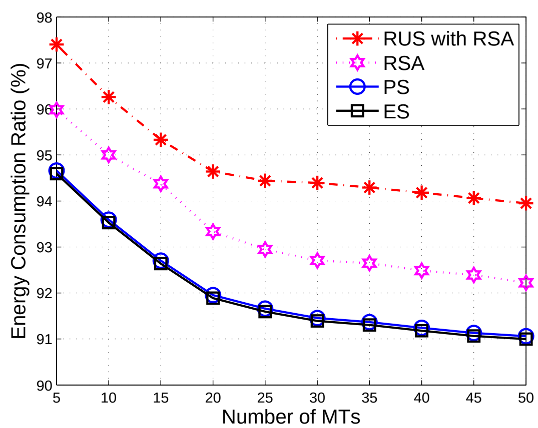

Fig. 6. Energy efficiency performance of whole system

Fig. 6 presents the energy efficiency performance of the whole system including the BS and MTs. As we can observe, the proposed WeCMC is able to obtain energy saving gain compared to the conventional multicasting scheme, though the energy saving gain is not strong (about 9%). The advantages of our presented user scheduling and subchannel location schemes (PS) can also be observed. These advantages are due to the fact that the proposed WeCMC structure is mainly for saving energy from the terminal sides. We also have plotted the results obtained by exhaustive searching of DORs and subchannels (ES), which is considered to be the optimal

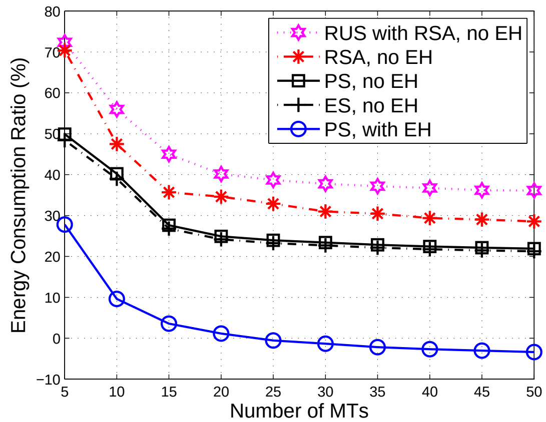

Fig. 7. Energy efficiency performance of the MTs

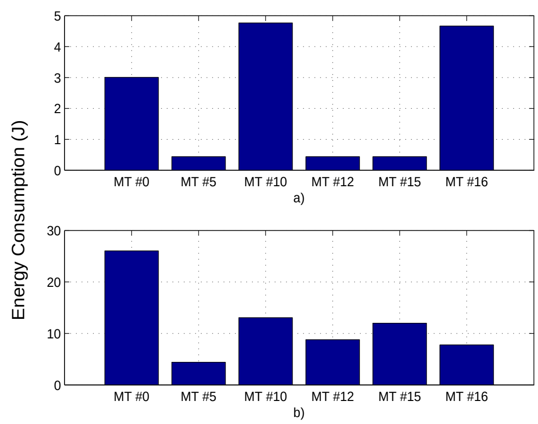

Fig. 8. Energy efficiency performance of MTs, a snapshot

scheme for finding DORs and subchannels. As we can observe the performance of our proposed scheme is very close to the optimal one. The comparison of ES and PS confirms the efficiency of the proposed user scheduling and subchannel allocation algorithms. It is worth noticing that although the proposed scheme can also bring benefits for the BS as it only needs to transmit to several DORs instead of multicasting to all, the energy saving gain is not remarkable from the point-of-view of the whole system.

As mentioned, the primary task of WeCMC is to save energy at the terminal side, so in Fig. 7, the energy saving performance is illustrated with the exclusion of the energy consumption of the BS. Moreover, in order to see the wireless power transfer impact, we show the performance with/without energy harvesting. As in Fig. 1, it can be observed that the proposed scheme can obtain significant energy saving gains even without energy harvesting at the MT side, and the proposed scheme has the performance similar to that of the optimal one. In addition, the wireless power transfer feature can further improve energy efficiency performance. In the current setting, the whole group of MTs can harvest more energy than it costs, which evidences the significance of the SWIPT technique.

In Fig. 8, a snapshot is presented to illustrate the energy consumption performance of different WeCMC MTs during the scheduling procedure. In Fig. 8a, the energy consumption performance of a stand-alone MT (MT $\#0$) and some of the WeCMC MTs are presented considering one single data segment transmission. MTs $\#10$ and $\#16$ in Fig. 8a are the scheduled DORs in this case. We can see that for a single data segment transmission, due to the transmit power consumption inside WeCMC, the energy consumption of the DORs is higher than that of the stand-alone UE who is using conventional multicasting transmission. In Fig. 8b, the energy consumption of the MTs for receiving 10 assigned data segment is presented. With 10 assigned data segments, several MTs have been scheduled, and the individual energy consumption of every WeCMC MT is lower than that of the stand-alone MT, which confirms the advantages of the WeCMC model and the presented schemes.

VI. Conclusion

In this work, we investigated the problem of energy efficient resource allocation for the wireless power transfer enabled collaborative mobile clouds. We presented a theoretical analysis on the energy consumption of the MTs within the cloud. Moreover, user scheduling schemes were introduced in order to investigate when and how many users should participate in receiving from the BS in order to improve energy efficiency. Accordingly, subchannel and power allocation schemes were proposed with the objective to minimize the energy consumption of the considered system. The simulation results demonstrated the energy saving benefits of a mobile cloud and also illustrated the advantages of advocating wireless power transfer for the mobile cloud.

Appendix A

Proof of Theorem 1

We assume that the subchannels i and j are allocated to the scheduled DORs $\mathcal{K}$ optimally for the transmission process. Then, we can separately prove the necessary condition and sufficient condition of the Theorem 1.

1) First, we prove the necessary condition. Suppose Υ is the solution set. Let $\boldsymbol{\omega}_0$ and $\boldsymbol{\upsilon}_0$ be the solutions of (20). Then we have

$$q_0 = \frac{U_c(\boldsymbol{\omega}_0, \boldsymbol{\upsilon}_0)}{R_c(\boldsymbol{\omega}_0, \boldsymbol{\upsilon}_0)} \leq \frac{U_c(\boldsymbol{\omega}, \boldsymbol{\upsilon})}{R_c(\boldsymbol{\omega}, \boldsymbol{\upsilon})}, \forall \boldsymbol{\omega}, \boldsymbol{\upsilon} \in \Upsilon. \quad (43)$$

Consequently, we can arrive in

$$U_c(\boldsymbol{\omega}, \boldsymbol{\upsilon}) - q_0 R_c(\boldsymbol{\omega}, \boldsymbol{\upsilon}) \geq 0, \forall \boldsymbol{\omega}, \boldsymbol{\upsilon} \in \Upsilon, \quad (44)$$

and

$$U_c(\boldsymbol{\omega}_0, \boldsymbol{\upsilon}_0) - q_0 R_c(\boldsymbol{\omega}_0, \boldsymbol{\upsilon}_0) = 0, \forall \boldsymbol{\omega}_0, \boldsymbol{\upsilon}_0 \in \Upsilon. \quad (45)$$

From (44) we see that $min\{U_c(\boldsymbol{\omega}, \boldsymbol{\upsilon}) - q_0 R_c(\boldsymbol{\omega}, \boldsymbol{\upsilon}) | \boldsymbol{\omega}, \boldsymbol{\upsilon} \in \Upsilon\} = 0$. From (45) we observe that the minimum value is taken when $\{\boldsymbol{\omega}, \boldsymbol{\upsilon}\} = \{\boldsymbol{\omega}_0, \boldsymbol{\upsilon}_0\}$. Therefore, the necessary condition can be proved.

2) To prove the sufficient condition, let $\{\boldsymbol{\omega}_0, \boldsymbol{\upsilon}_0\}$ be a solution of (21), such that $U_c(\boldsymbol{\omega}_0, \boldsymbol{\upsilon}_0) - q_0 R_c(\boldsymbol{\omega}_0, \boldsymbol{\upsilon}_0) = 0$ then we have

$$\begin{aligned} &U_c(\boldsymbol{\omega}, \boldsymbol{\upsilon}) - q_0 R_c(\boldsymbol{\omega}, \boldsymbol{\upsilon}) \geq \\ &U_c(\boldsymbol{\omega}_0, \boldsymbol{\upsilon}_0) - q_0 R_c(\boldsymbol{\omega}_0, \boldsymbol{\upsilon}_0) = 0, \forall \boldsymbol{\omega}, \boldsymbol{\upsilon} \in \Upsilon. \end{aligned} \tag{46}$$

Hence

$$U_c(\boldsymbol{\omega}, \boldsymbol{\upsilon}) - q_0 R_c(\boldsymbol{\omega}, \boldsymbol{\upsilon}) \geq 0, \forall \boldsymbol{\omega}, \boldsymbol{\upsilon} \in \Upsilon, \tag{47}$$

and

$$U_c(\boldsymbol{\omega}_0, \boldsymbol{\upsilon}_0) - q_0 R_c(\boldsymbol{\omega}_0, \boldsymbol{\upsilon}_0) = 0, \forall \boldsymbol{\omega}_0, \boldsymbol{\upsilon}_0 \in \Upsilon. \tag{48}$$

From (47) we have $\frac{U_c(\boldsymbol{\omega}, \boldsymbol{\upsilon})}{R_c(\boldsymbol{\omega}, \boldsymbol{\upsilon})} \geq q_0, \forall \boldsymbol{\omega}, \boldsymbol{\upsilon} \in \Upsilon$, that is q_0 is the minimum of (20). From (48) we have $\frac{U_c(\boldsymbol{\omega}_0, \boldsymbol{\upsilon}_0)}{R_c(\boldsymbol{\omega}_0, \boldsymbol{\upsilon}_0)} = q_0$, that is $\{\boldsymbol{\omega}_0, \boldsymbol{\upsilon}_0\}$ is a solution of (20).

APPENDIX B

Proof of Convergence of Algorithm 1

Similar procedure as shown in [23] can be applied to prove the convergence of the Algorithm 1. For simplicity, assuming that

$$f(q') = \min_{\boldsymbol{\beta}, \boldsymbol{\omega}, \boldsymbol{\upsilon}} U_c(\boldsymbol{\beta}, \boldsymbol{\omega}, \boldsymbol{\upsilon}) - q' R_c(\boldsymbol{\beta}, \boldsymbol{\omega}, \boldsymbol{\upsilon}). \tag{49}$$

Then assuming $q^{\backprime} > q'$ and considering two optimal resource allocation policies, $\{\boldsymbol{\beta}^{\backprime}, \boldsymbol{\omega}^{\backprime}, \boldsymbol{\upsilon}^{\backprime}\}$ and $\{\boldsymbol{\beta}', \boldsymbol{\omega}', \boldsymbol{\upsilon}'\}$ for $f(q^{\backprime})$ and $f(q')$, respectively, we have

$$\begin{aligned} f(q^{\backprime}) &= \min_{\boldsymbol{\beta}, \boldsymbol{\omega}, \boldsymbol{\upsilon}} U_c(\boldsymbol{\beta}, \boldsymbol{\omega}, \boldsymbol{\upsilon}) - q^{\backprime} R_c(\boldsymbol{\beta}, \boldsymbol{\omega}, \boldsymbol{\upsilon}) \\ &= U_c(\boldsymbol{\beta}^{\backprime}, \boldsymbol{\omega}^{\backprime}, \boldsymbol{\upsilon}^{\backprime}) - q^{\backprime} R_c(\boldsymbol{\beta}^{\backprime}, \boldsymbol{\omega}^{\backprime}, \boldsymbol{\upsilon}^{\backprime}) \\ &< U_c(\boldsymbol{\beta}', \boldsymbol{\omega}', \boldsymbol{\upsilon}') - q^{\backprime} R_c(\boldsymbol{\beta}', \boldsymbol{\omega}', \boldsymbol{\upsilon}') \\ &\leq U_c(\boldsymbol{\beta}', \boldsymbol{\omega}', \boldsymbol{\upsilon}') - q' R_c(\boldsymbol{\beta}', \boldsymbol{\omega}', \boldsymbol{\upsilon}') \\ &= f(q'). \end{aligned} \tag{50}$$

Therefore, we can see that $f(q)$ is a strong monotonic decreasing function, i.e. $f(q^{\backprime}) < f(q')$, if $q^{\backprime} > q'$. Suppose $\{\boldsymbol{\beta}^l, \boldsymbol{\omega}^l, \boldsymbol{\upsilon}^l\}$ is the optimal resource allocation policy in the lth iteration and $q^l \neq q^*$ and $q^{l+1} \neq q^*$. We can observe that $q^l > 0$ and $q^{l+1} > 0$. Since we obtain $q^{l+1} = U_c(\boldsymbol{\beta}^l, \boldsymbol{\omega}^l, \boldsymbol{\upsilon}^l)/R_c(\boldsymbol{\beta}^l, \boldsymbol{\omega}^l, \boldsymbol{\upsilon}^l)$ in Alg. 1, we can arrive to

$$\begin{aligned} f(q^l) &= U_c(\boldsymbol{\beta}^l, \boldsymbol{\omega}^l, \boldsymbol{\upsilon}^l) - q^l R_c(\boldsymbol{\beta}^l, \boldsymbol{\omega}^l, \boldsymbol{\upsilon}^l) \\ &= R_c(\boldsymbol{\beta}^l, \boldsymbol{\omega}^l, \boldsymbol{\upsilon}^l)(q^{l+1} - q^l). \end{aligned} \tag{51}$$

As $f(q^l) > 0$ and $R_c(\boldsymbol{\beta}^l, \boldsymbol{\omega}^l, \boldsymbol{\upsilon}^l) > 0$, we have $q^{l+1} > q^l$. Therefore, we can see that as long as the number of iterations is large enough, $f(q^l) \to 0$ and $f(q^l)$ satisfies the optimality condition as presented in **Theorem 1**. To this end, the convergence of Algorithm 1 can be proved.

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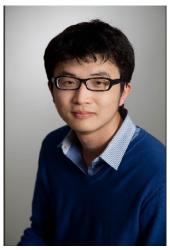

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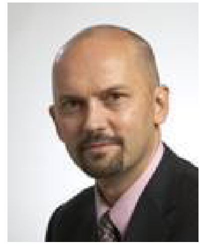

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